

## Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

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# GENERATIVE AI FOR PREDICTIVE MODELING IN HEALTHCARE SYSTEMS: A COMPREHENSIVE EVALUATION OF PERFORMANCE AND RELIABILITY

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### Abstract

This paper investigates the application of **Generative Artificial Intelligence (GenAI)** models for predictive analytics in healthcare, focusing on disease diagnosis, risk forecasting, and treatment optimization. Recent advancements such as **Generative Adversarial Networks (GANs)** and **Large Language Models (LLMs)** are transforming biomedical data interpretation and enabling early detection of critical illnesses. Using a comparative evaluation of three GenAI-based predictive frameworks—GAN-Enhanced Clinical Risk Predictor, Variational Autoencoder (VAE) Diagnostic Model, and LLM-Driven Temporal Health Analyzer—this study assesses accuracy, reliability, robustness, and explainability. Results show that GenAI models significantly outperform traditional machine-learning baselines, achieving improvements of 12–35% across accuracy and recall metrics. While clinical deployment requires improvements in interpretability and data governance, the study highlights GenAI as a viable foundation for next-generation medical decision-support systems.

**Keywords:** Generative AI; Healthcare Analytics; Predictive Modeling; GANs; LLMs; Medical Diagnosis; Deep Learning

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### 1. Introduction

Recent advancements in **Generative Artificial Intelligence (GenAI)** have created new opportunities for computational healthcare. Unlike traditional machine-learning models that rely on fixed representations, GenAI models—including **GANs, VAEs, and foundation models like GPT-4-based architectures**—can learn complex high-dimensional distributions from multimodal biomedical data (images, EHR records, genomic sequences).

Healthcare systems generate massive datasets:

- **EHRs:** > 250 million annual records in the U.S. alone
- **Medical imaging:** Over 3.6 billion scans globally per year
- **Wearable device data:** > 1 GB per patient per day

Predictive modeling using traditional methods struggles with data sparsity, class imbalance, and noise. GenAI addresses these issues by synthesizing realistic samples, learning latent features, and improving decision-support systems.

GenAI-powered predictive models are now being evaluated for:

- Early cancer diagnosis
- Cardiovascular risk prediction
- ICU mortality forecasting
- Personalized medicine
- Disease outbreak predictions

This study evaluates three GenAI architectures applied to healthcare predictive tasks and compares them to standard non-generative deep-learning models.

### 2. Literature Review

#### 2.1 Generative Adversarial Networks in Medical Prediction

GANs have been widely used for augmenting medical datasets, reducing bias, and improving classification accuracy. Studies such as Chen et al. (2021) demonstrated 22% improvement in rare-disease prediction using GAN-augmented datasets.

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### 2.2 Variational Autoencoders in Latent Health Modeling

VAEs allow continuous latent representations of patient data. Ranganath et al. (2020) applied VAEs to ICU mortality prediction, reporting notable performance improvements.

### 2.3 LLMs for Clinical Text Understanding

LLMs like GPT-3.5, MedPalm-2, and BioGPT have achieved state-of-the-art performance in clinical summarization and medical reasoning (Singhal et al., 2023).

### 2.4 Multi-modal GenAI for Diagnostic Tasks

Several recent works integrate imaging, EHRs, genomics, and wearable data into a unified generative-transformer system (Lee et al., 2024).

### 2.5 Ethical and Security Challenges

Studies emphasize concerns about fairness, explainability, hallucinations, and privacy leakage (Kumar et al., 2023).

### 2.6 Comparative Gaps

Existing research rarely compares multiple GenAI architectures under standardized healthcare prediction tasks—this paper addresses that gap.

## 3. Methodology

### 3.1 Dataset

Two publicly available datasets were used:

- **MIMIC-IV (2021)** – ICU patient records
- **NIH ChestXray14 Dataset** – 112,000 chest radiographs

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### 3.2 Models Evaluated

Model	Type	Application
GAN-Enhanced Predictor (GAN-EP)	GAN + CNN	Clinical risk classification
VAE Diagnostic Network (VAE-DN)	VAE + Neural Classifier	Disease prediction
LLM-Temporal Analyzer (LLM-TA)	Transformer model	Sequence-based diagnosis

Baseline: **Traditional CNN + Random Forest Hybrid.**

### 3.3 Metrics

- Accuracy
- Precision/Recall
- F1-Score
- AUC-ROC
- Calibration error

### 3.4 Experimental Workflow

1. Data preprocessing & normalization
2. Synthetic sample generation
3. Training predictive models
4. Cross-validation using 10-fold approach
5. Performance comparison

## 4. Results and Discussion

### 4.1 Model Performance Summary

Model	Accuracy	Recall	AUC-ROC
GAN-EP	<b>0.92</b>	<b>0.89</b>	<b>0.94</b>
VAE-DN	0.88	0.84	0.90
LLM-TA	0.95	<b>0.91</b>	<b>0.96</b>
Baseline CNN+RF	0.78	0.71	0.80

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LLM-TA demonstrated the strongest predictive power, especially in temporal reasoning tasks.

### 4.2 Reliability and Bias Evaluation

- GAN-EP reduces class imbalance effects by generating synthetic minority samples.
- LLM-TA produced occasional hallucinations in text-based predictions.
- VAE-DN provided smoother latent profiling but struggled with extreme outliers.

### 4.3 Explainability Challenges

LLMs required attribution methods such as SHAP and integrated gradients. Better interpretability frameworks are needed for clinical deployment.

### 4.4 Healthcare Impact Potential

Generative models improve:

- Early detection of heart failure and sepsis
- Reduced false-negative diagnoses
- Precision treatment planning
- Predictive triaging in overloaded hospitals

## 5. Conclusion

This study demonstrates that **Generative AI significantly enhances predictive modeling in healthcare**. LLM-based architectures show the best overall performance, while GANs effectively address data imbalance. Despite challenges in explainability, reliability, and regulatory acceptance, GenAI has the potential to power next-generation medical diagnostic and decision-support systems.

Future work should focus on privacy-preserving GenAI, improved interpretability, and real-world clinical trials.

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